

# COVID in MA analyzer

## Introduction and citations

### Data sources

I'm using the wiki compilation at [https://en.wikipedia.org/wiki/2020\\_coronavirus\\_pandemic\\_in\\_Massachusetts](https://en.wikipedia.org/wiki/2020_coronavirus_pandemic_in_Massachusetts) which gives confirmed cases of COVID-19 in Massachusetts, according ultimately to the daily updates from the MA Dept of Public Health, such as <https://www.mass.gov/doc/covid-19-cases-in-massachusetts-as-of-march-28-2020/download>.

### Subsidiary factoids:

#### Population of Boston:

```
pop_yr=[2010, 2017];
pop_pp=[620702,685094];
pop_2020_bos=diff(pop_pp)/diff(pop_yr)*3+pop_pp(2)
```

```
pop_2020_bos = 7.1269e+05
```

#### Population of Massachusetts:

```
pop_yr=[2005, 2018];
pop_pp=[6.454e6,6.902e6];
pop_2020_ma=diff(pop_pp)/diff(pop_yr)*2+pop_pp(2)
```

```
pop_2020_ma = 6.9709e+06
```

### Intent

Just to have an idea of when we should see a peak.

### Data sets and structure

Data are given in the table Cov\_Ma.

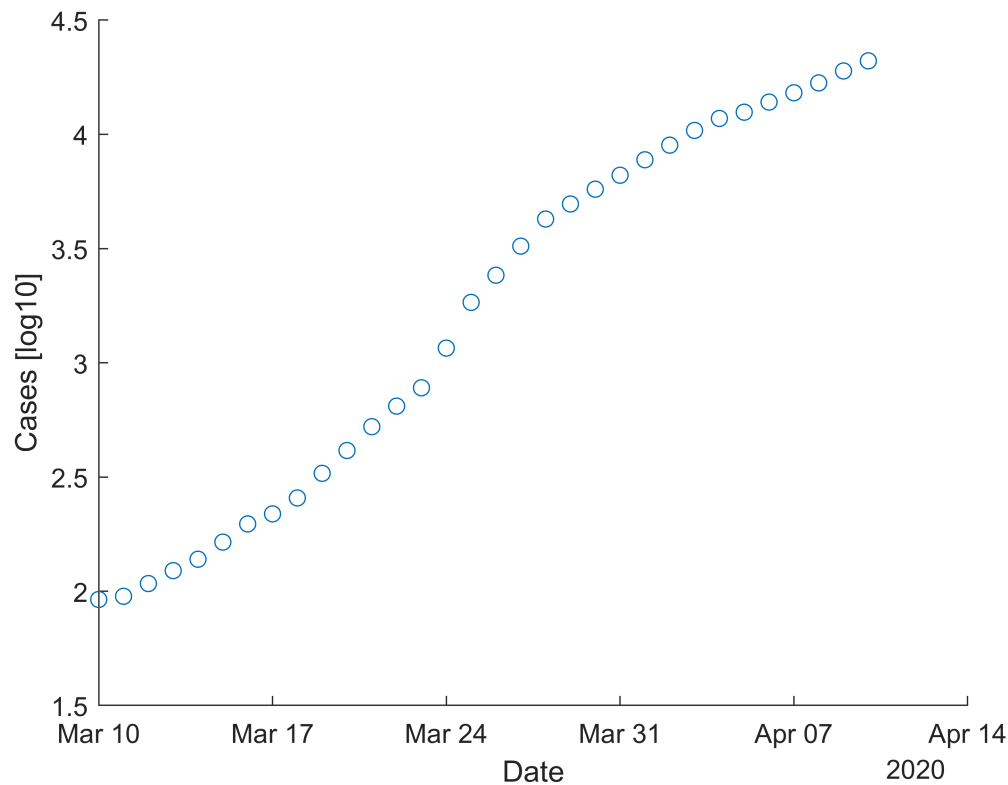
```
Cov_Ma.Properties.VariableNames
```

```
ans = 1x12 cell array
```

```
    {'Days_since_Mar_10'}    {'Cases'}    {'Date'}    {'Cases_change'}    {'Cases_growth'}    {'Tests'}    {'Tests_...
```

### Just the facts, ma'am

```
figure
scatter(Cov_Ma.Date, log10(Cov_Ma.Cases))
ylabel('Cases [log10]')
xlabel('Date')
```



## Fitting the data to a logistic curve

The logistic curve is given by

$$m_i = \frac{k_i}{1 + e^{-\gamma(t-t_0)}}$$

where  $m_i$  is a measure of COVID (I use identified cases and identified deaths),  $t$  is the number of days since March 10 (a reasonable measure of when community spreading started),  $t_0$  is the midpoint of the growth (measured in days since March 10), and  $\gamma$  is a constant related to growth rate.

One must initialize the vector of constants with initial conditions to begin the minimization that finds the best-fitting array of constants. These are determined by trial and error. Good practice is to use a variety of IC to make sure the solution is robust. The ICs are in array `beta0_i`. MATLAB makes fitting the model pretty easy.

## Fits

### Cases

```
modelfun_c = @(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))
```

`modelfun_c` = function\_handle with value:

```
@(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))
```

```
beta0_c = [40000 50 0.05];
```

```
mdl_c = fitnlm(Cov_Ma.Days_since_Mar_10,Cov_Ma.Cases,modelfun_c,beta0_c)
```

```
mdl_c =
```

```
Nonlinear regression model:
```

```
y ~ F(b,x)
```

```
Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
<b>b1</b>	28515	1807.4	15.777	9.0713e-16
<b>b2</b>	26.893	0.6596	40.772	3.6793e-27
<b>b3</b>	0.21206	0.010027	21.149	3.5941e-19

```
Number of observations: 32, Error degrees of freedom: 29
```

```
Root Mean Squared Error: 412
```

```
R-Squared: 0.996, Adjusted R-Squared 0.996
```

```
F-statistic vs. zero model: 4.28e+03, p-value = 1.81e-38
```

## Deaths

```
modelfun_d = @(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))
```

```
modelfun_d = function_handle with value:
```

```
@(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))
```

```
beta0_d = [100 20 0.222];
```

```
mdl_d = fitnlm(Cov_Ma.Days_since_Mar_10,Cov_Ma.Deaths,modelfun_d,beta0_d)
```

```
mdl_d =
```

```
Nonlinear regression model:
```

```
y ~ F(b,x)
```

```
Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
<b>b1</b>	2023.3	670.27	3.0187	0.0052485
<b>b2</b>	34.948	2.2819	15.315	1.9615e-15
<b>b3</b>	0.22211	0.013955	15.916	7.2063e-16

```
Number of observations: 32, Error degrees of freedom: 29
```

```
Root Mean Squared Error: 11.7
```

```
R-Squared: 0.995, Adjusted R-Squared 0.995
```

```
F-statistic vs. zero model: 2.86e+03, p-value = 6.12e-36
```

## Predictions

```
Pred_window=21;
```

```
Pred_days=0:max(Cov_Ma.Days_since_Mar_10)+Pred_window;
```

```
Pred_dates=(min(Cov_Ma.Date):days(1):max(Cov_Ma.Date)+days(Pred_window))';
```

```
[Cov_Ma_Pred.cases, Cov_Ma_Pred.casesci]=predict(mdl_c,Pred_days','Prediction','observation');
```

```
[Cov_Ma_Pred.deaths, Cov_Ma_Pred.deathsci]=predict(mdl_d,Pred_days','Prediction','observation');
```

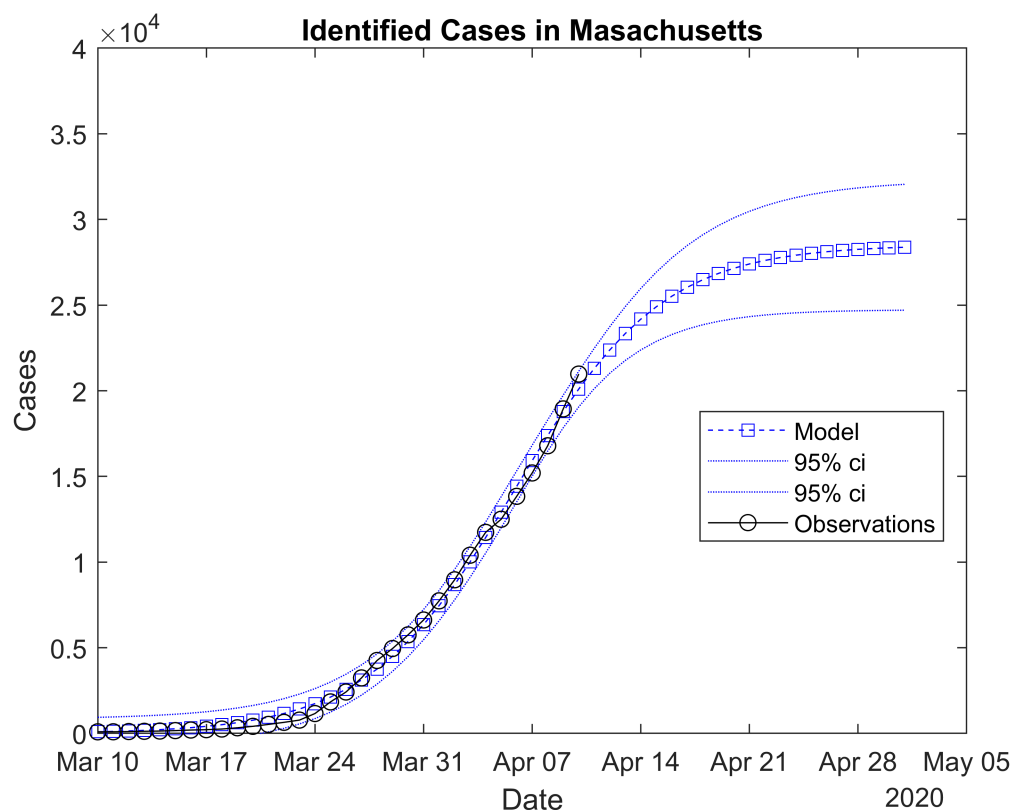
## Graph the data and the models up

### Cases

```
figure
plot(Pred_dates,Cov_Ma_Pred.cases,'--bs')
hold
```

Current plot held

```
plot(Pred_dates,Cov_Ma_Pred.casesci(:,1),'b')
plot(Pred_dates,Cov_Ma_Pred.casesci(:,2),'b')
plot(Cov_Ma.Date,Cov_Ma.Cases, '-ko')
ylabel('Cases')
xlabel('Date')
ylim([0,40000])
title('Identified Cases in Massachusetts')
legend('Model','95% ci','95% ci','Observations', 'location', 'best')
```



### Deaths

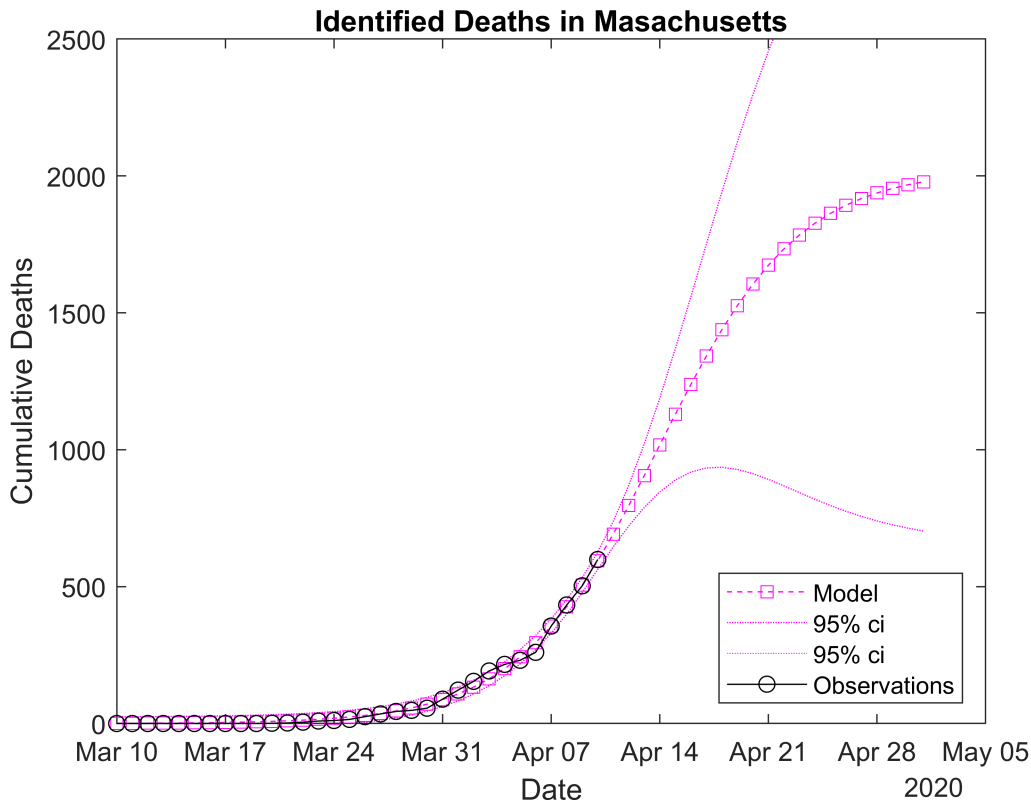
```
figure
plot(Pred_dates,Cov_Ma_Pred.deaths,'--ms')
hold
```

Current plot held

```

plot(Pred_dates,Cov_Ma_Pred.deathsci(:,1),'m')
plot(Pred_dates,Cov_Ma_Pred.deathsci(:,2),'m')
plot(Cov_Ma.Date,Cov_Ma.Deaths,'-ko')
ylabel('Cumulative Deaths')
xlabel('Date')
ylim([0,2500])
title('Identified Deaths in Massachusetts')
legend('Model','95% ci','95% ci','Observations', 'location', 'best')

```



## When are the peaks?

Take the differences in the cumulative graphs and plot them up to see the peaks.

```

figure
yyaxis right
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.deaths),'Color', [.94 .5 .5], 'LineStyle','-','Marker',
hold

```

Current plot held

```

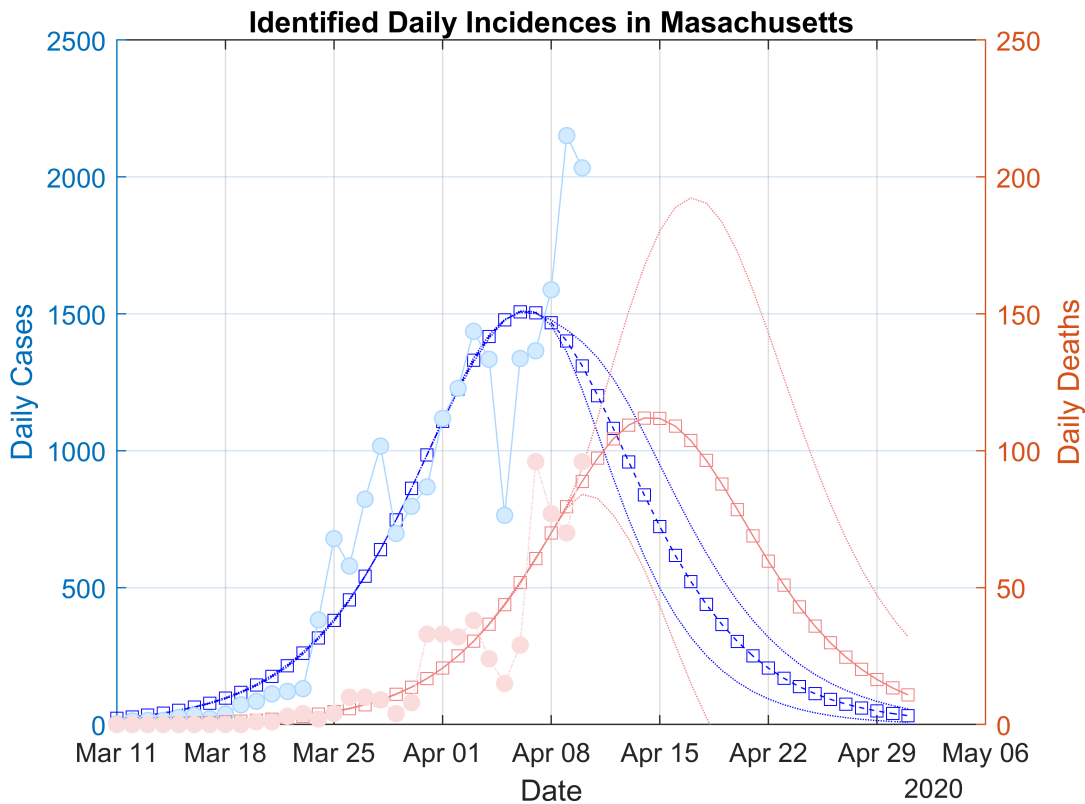
grid
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.deathsci(:,1)),'Color', [.94 .5 .5], 'LineStyle',':')
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.deathsci(:,2)),'Color', [.94 .5 .5], 'LineStyle',':')
plot(Cov_Ma.Date(2:end),diff(Cov_Ma.Deaths),'Color', [.98 .88 .88], 'MarkerFaceColor',[.98 .88
ylabel('Daily Deaths')
xlabel('Date')

```

```

ylim([0,250])
title('Identified Daily Incidences in Massachusetts')
%legend('Model','95% ci','95% ci','Observations', 'location', 'best')
yyaxis left
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.cases),'--bs')
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.casesci(:,1)),':b')
plot(Pred_dates(2:end),diff(Cov_Ma_Pred.casesci(:,2)),':b')
plot(Cov_Ma.Date(2:end),diff(Cov_Ma.Cases),'Color', [.68 .85 1], 'MarkerFaceColor', [.84 .92 1])
ylabel('Daily Cases')

```



```

%xlabel('Date')
%ylim([0,50])
%title('Identified Daily Incidences in Massachusetts')
%legend('Model','95% ci','95% ci','Observations', 'location', 'best')

```

## Using previous results to predict the short-term future

### Cases

```

modelfun_c = @(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))

```

modelfun\_c = *function\_handle* with value:

```

@(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))

```

```

for indx=15:Cov_Ma.Days_since_Mar_10(end)
    beta0_c = [18000 25 0.24];
    mdl_c = fitnlm(Cov_Ma.Days_since_Mar_10(1:indx),Cov_Ma.Cases(1:indx),modelfun_c,beta0_c);

```

end

Warning: Iteration limit exceeded. Returning results from final iteration.  
Warning: The Jacobian at the solution is ill-conditioned, and some model parameters may not be estimated well (they are not identifiable). Use caution in making predictions.  
Warning: Iteration limit exceeded. Returning results from final iteration.  
Warning: The Jacobian at the solution is ill-conditioned, and some model parameters may not be estimated well (they are not identifiable). Use caution in making predictions.  
Warning: Iteration limit exceeded. Returning results from final iteration.  
Warning: The Jacobian at the solution is ill-conditioned, and some model parameters may not be estimated well (they are not identifiable). Use caution in making predictions.  
Warning: Iteration limit exceeded. Returning results from final iteration.  
Warning: The Jacobian at the solution is ill-conditioned, and some model parameters may not be estimated well (they are not identifiable). Use caution in making predictions.  
Warning: Iteration limit exceeded. Returning results from final iteration.  
Warning: The Jacobian at the solution is ill-conditioned, and some model parameters may not be estimated well (they are not identifiable). Use caution in making predictions.

## Deaths

```
modelfun_d = @(b,x)b(1)./(1+exp(-(x-b(2))*b(3)))
```

modelfun\_d = *function\_handle with value:*  
    @(b,x)b(1)./(1+exp(-(x-b(2))\*b(3)))

```
beta0_d = [5000 40 0.222];  
mdl_d = fitnlm(Cov_Ma.Days_since_Mar_10,Cov_Ma.Deaths,modelfun_d,beta0_d)
```

mdl\_d =  
Nonlinear regression model:  
    y ~ F(b,x)

Estimated	Coefficients:			
	Estimate	SE	tStat	pValue
<b>b1</b>	2023.3	670.46	3.0178	0.0052601
<b>b2</b>	34.947	2.2822	15.313	1.9692e-15
<b>b3</b>	0.22211	0.013954	15.917	7.2019e-16

Number of observations: 32, Error degrees of freedom: 29  
Root Mean Squared Error: 11.7  
R-Squared: 0.995, Adjusted R-Squared 0.995  
F-statistic vs. zero model: 2.86e+03, p-value = 6.12e-36